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(54) **EVENT DETECTION THROUGH TEXT ANALYSIS USING DYNAMIC SELF EVOLVING/LEARNING MODULE**

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G06N 99/00	(2010.01)
G06F 17/27	(2006.01)

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(58) **Field of Classification Search**

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See application file for complete search history.

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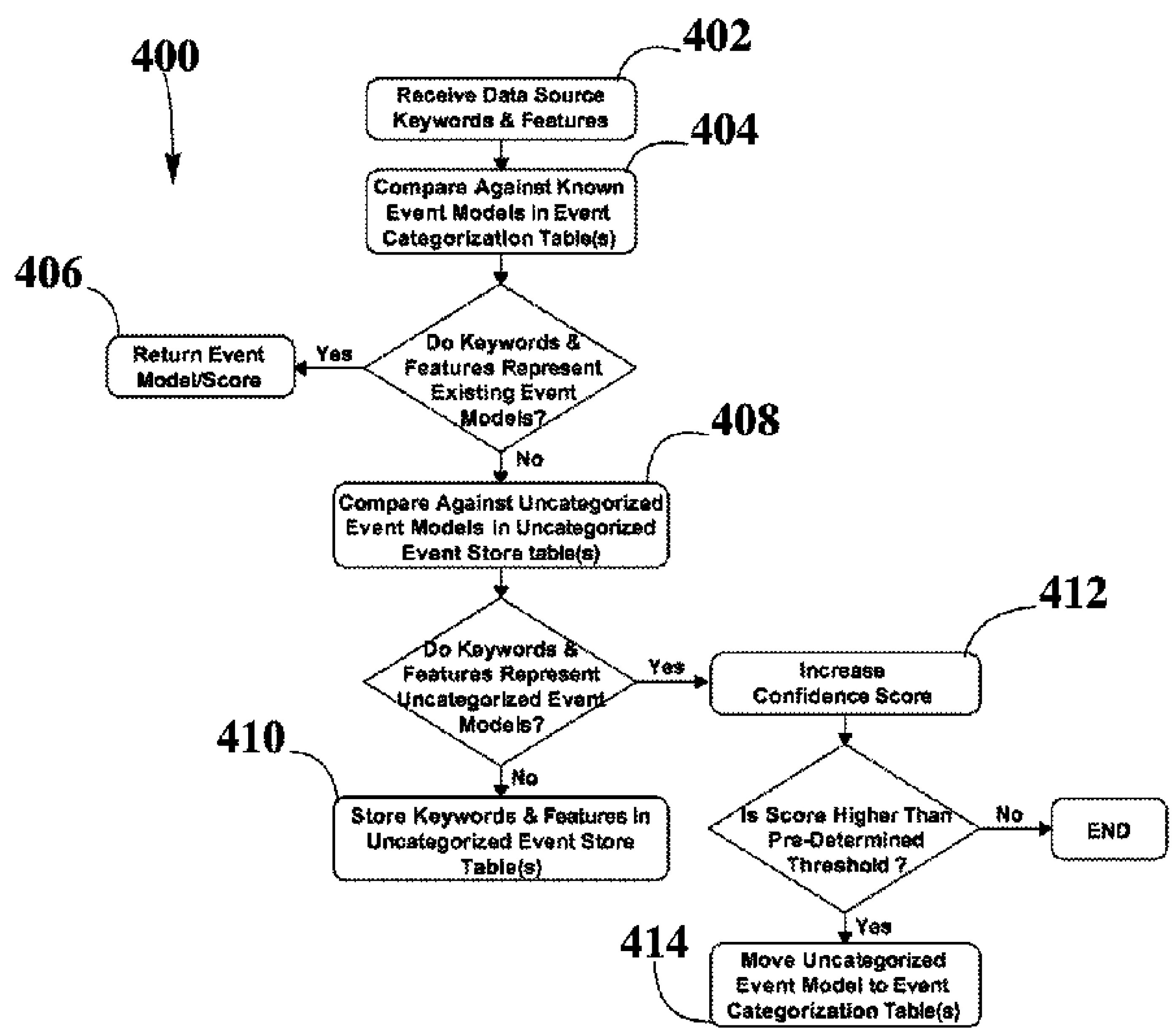
(57) **ABSTRACT**

A system and method for detecting events based on input data from a plurality of sources. The system may receive input from a plurality of sources containing information about possible events. A method for event detection involves pre-processing and normalizing a data input from a plurality of sources, extracting and disambiguating events and entities, associate event and entities, correlate events and entities associated from a data input to results from a different data source to determine if an event has occurred, and store the detected events in a data storage.

11 Claims, 6 Drawing Sheets



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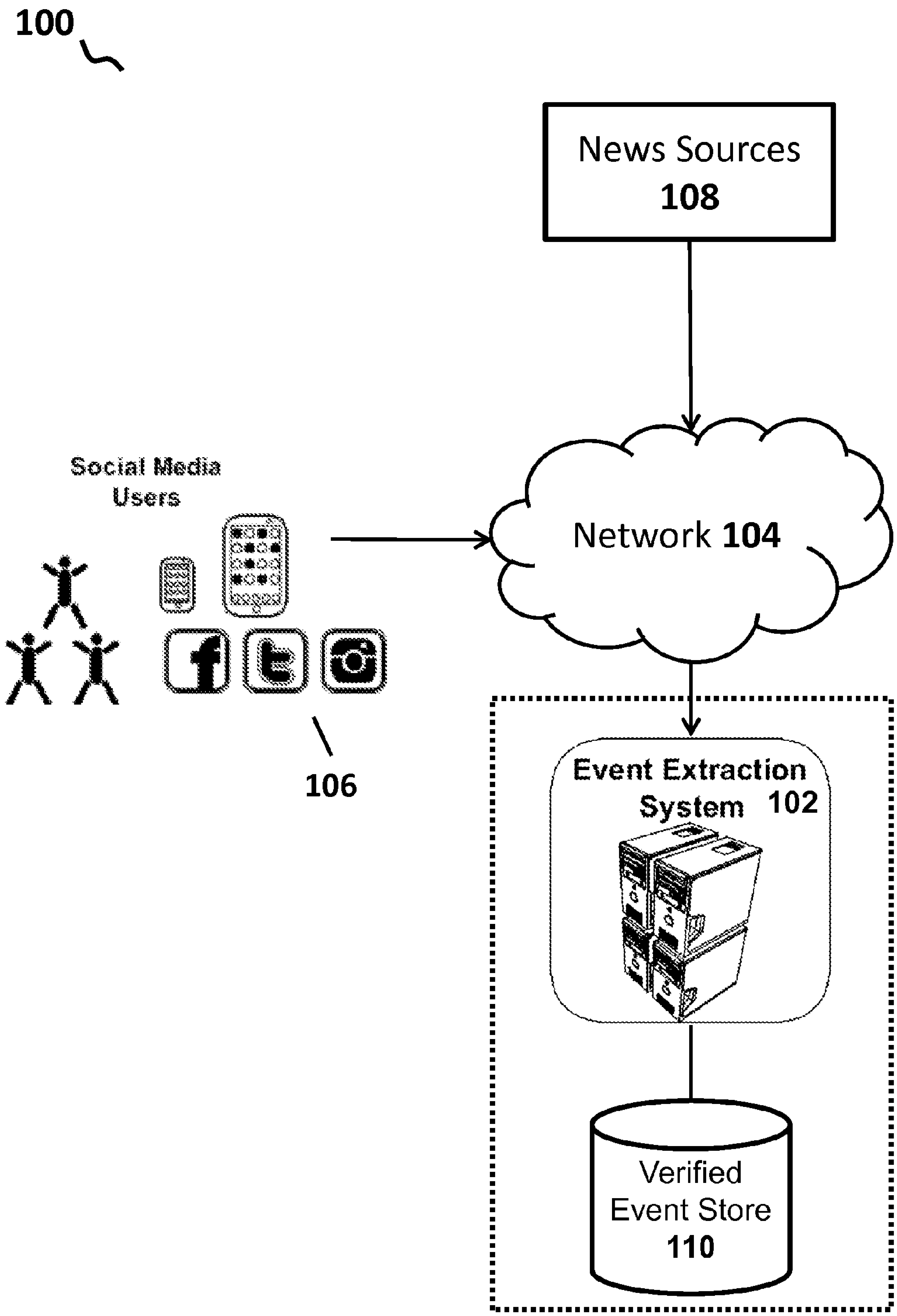
100
News Sources
108
Social Media
Users
Network 104
106
Event Extraction
System 102
Verified
Event Store
110

FIG. 1

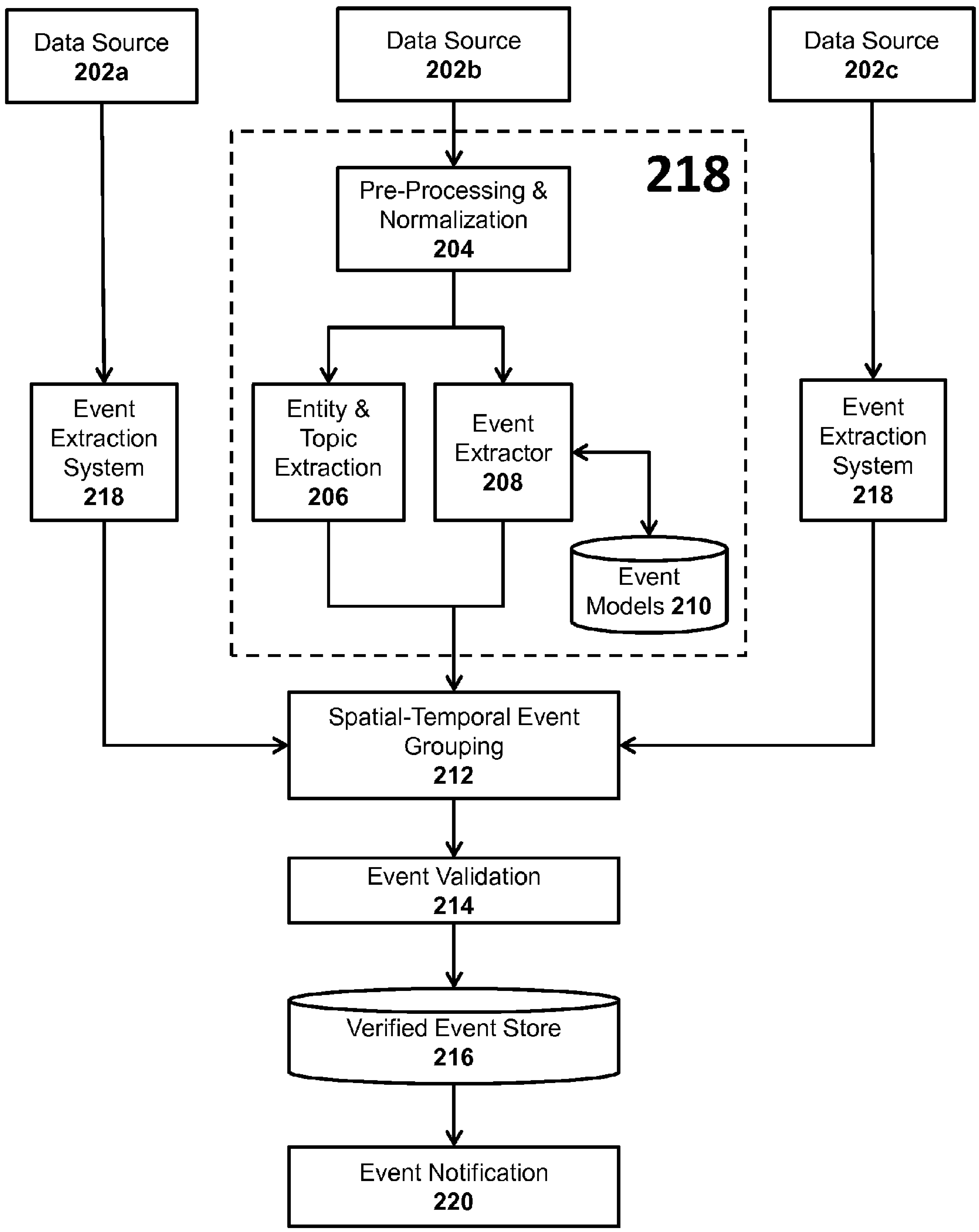
Data Source
202a
Data Source
202b
Data Source
202c
218
Pre-Processing &
Normalization
204
Event
Extraction
System
218
Entity &
Topic
Extraction
206
Event
Extractor
208
Event
Extraction
System
218
Event
Models 210
Spatial-Temporal Event
Grouping
212
Event Validation
214
Verified Event Store
216
Event Notification
220

FIG. 2

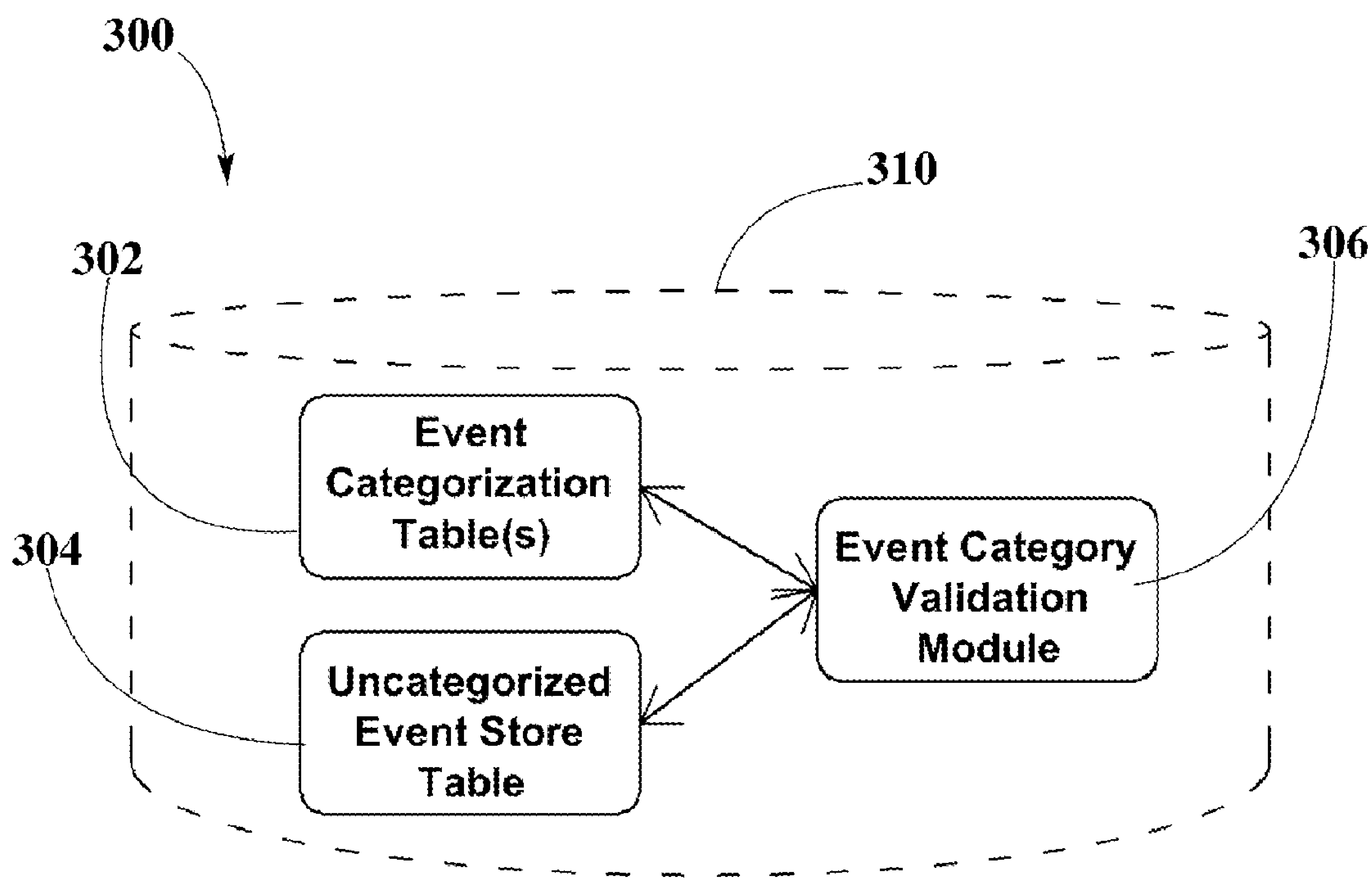
300
310
302
306
304
Event Categorization Table(s)
Event Category Validation Module
Uncategorized Event Store Table

FIG. 3

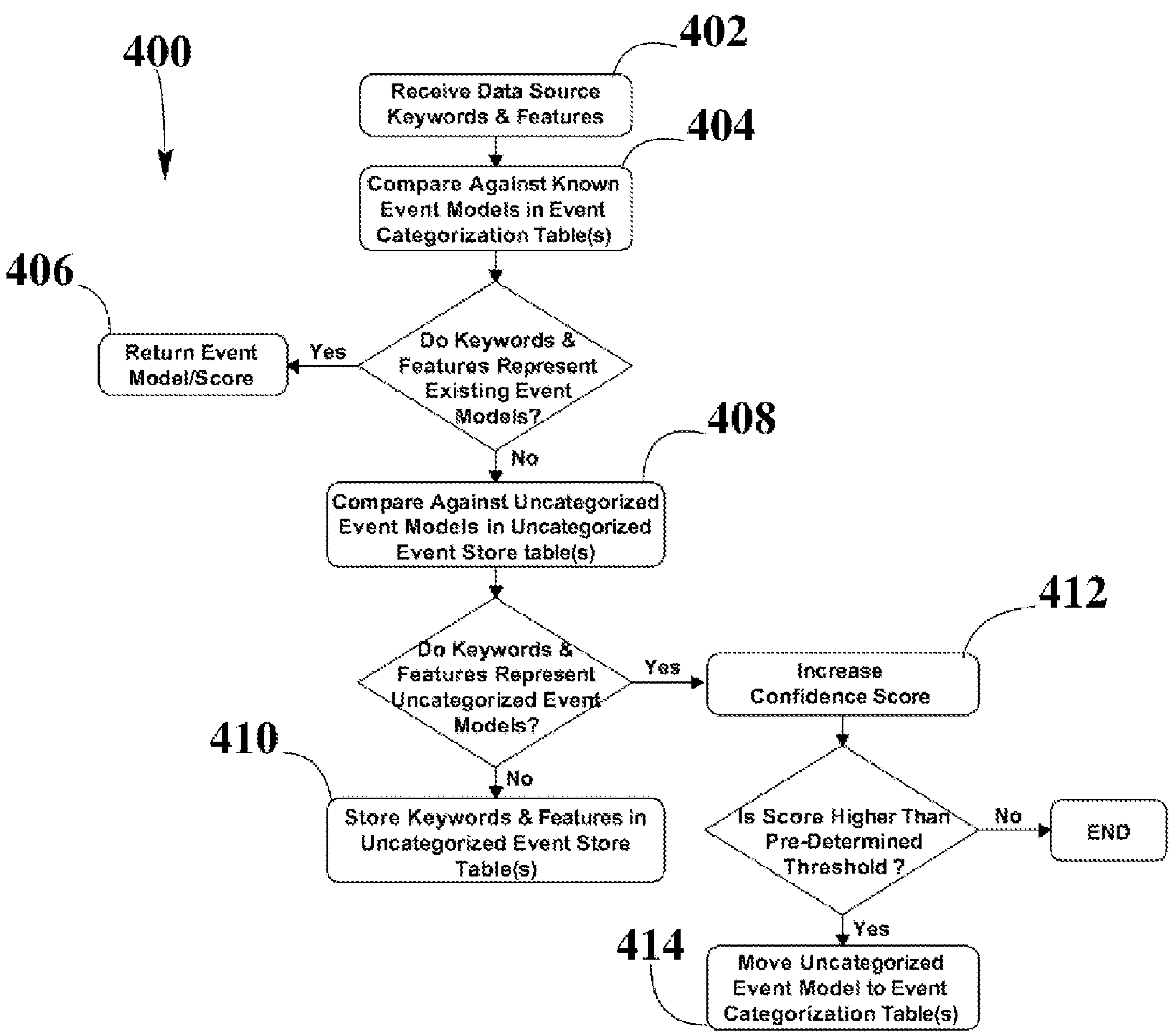
400
402
Receive Data Source Keywords & Features
404
Compare Against Known Event Models in Event Categorization Table(s)
406
Return Event Model/Score
Yes
Do Keywords & Features Represent Existing Event Models?
No
408
Compare Against Uncategorized Event Models In Uncategorized Event Store table(s)
412
Do Keywords & Features Represent Uncategorized Event Models?
Yes
Increase Confidence Score
410
No
Store Keywords & Features in Uncategorized Event Store Table(s)
Is Score Higher Than Pre-Determined Threshold ?
No
END
Yes
414
Move Uncategorized Event Model to Event Categorization Table(s)

FIG. 4

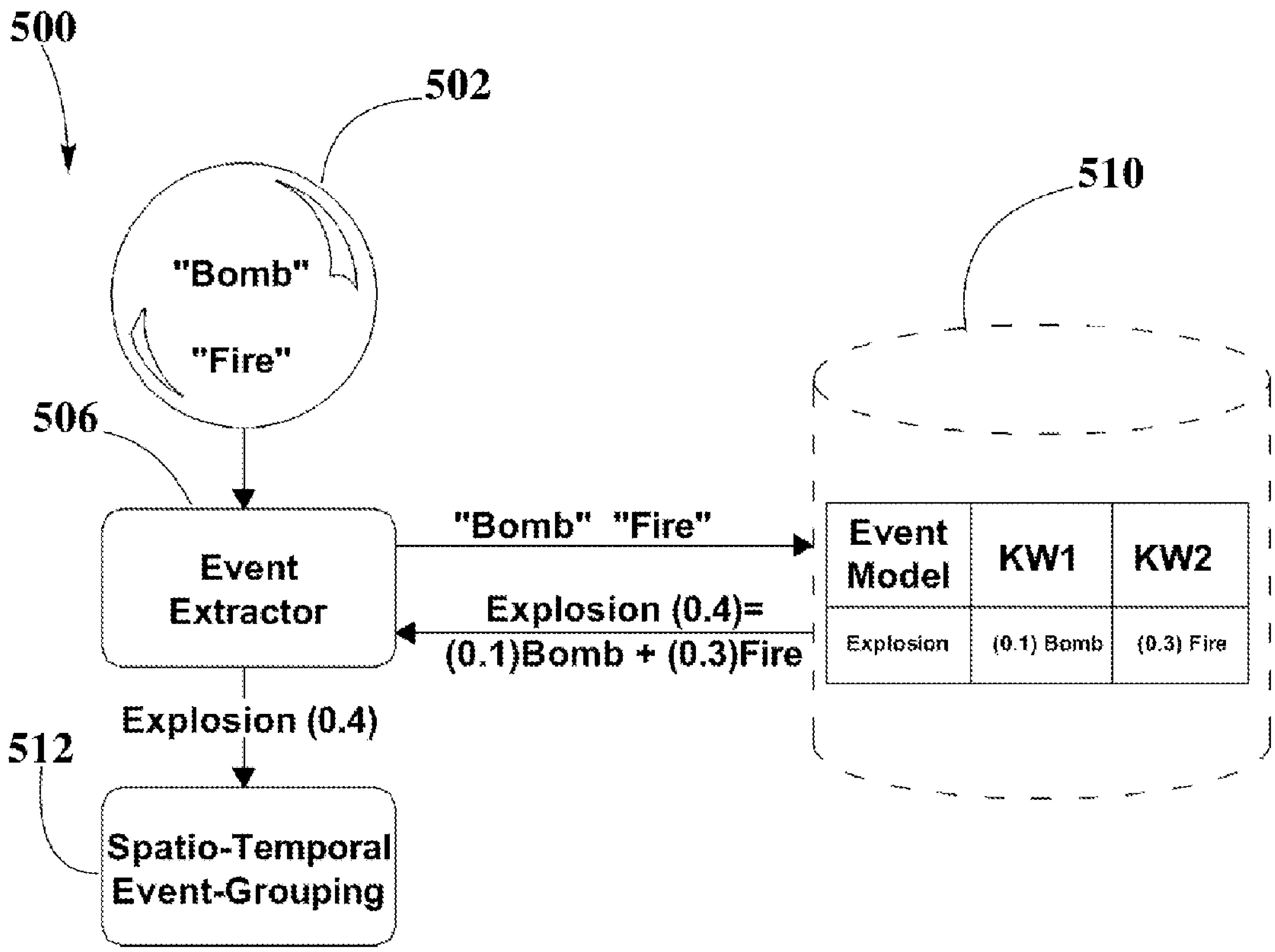
500
502
"Bomb"
"Fire"
506
Event Extractor
"Bomb" "Fire"
Explosion (0.4)=
(0.1)Bomb + (0.3)Fire
510
Event Model
KW1
KW2
Explosion
(0.1) Bomb
(0.3) Fire
Explosion (0.4)
512
Spatio-Temporal Event-Grouping

FIG. 5

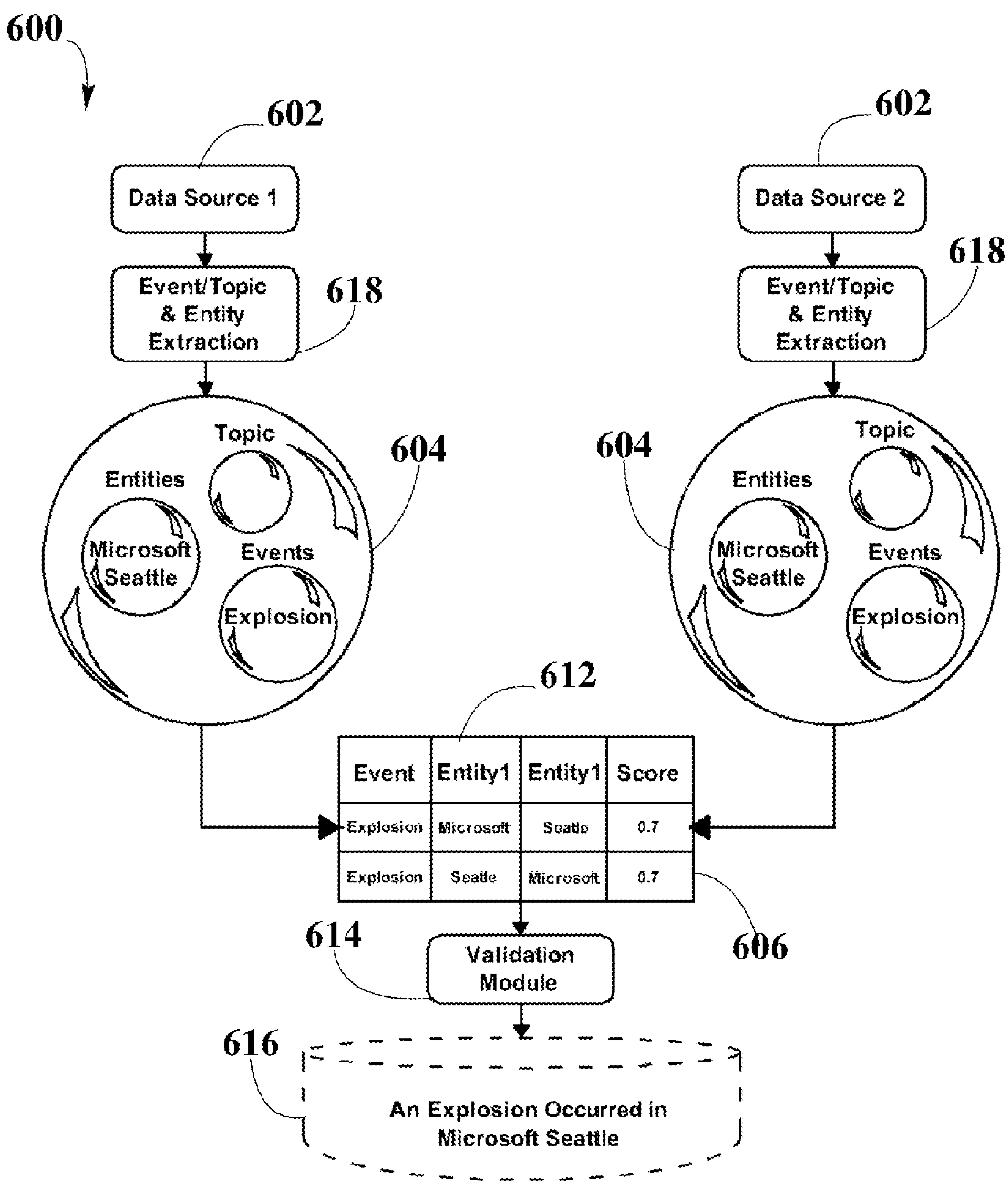
600
602
Data Source 1
602
Data Source 2
Event/Topic
& Entity
Extraction
618
Event/Topic
& Entity
Extraction
618
604
Topic
Entities
Microsoft
Seattle
Events
Explosion
604
Topic
Entities
Microsoft
Seattle
Events
Explosion
612
Event
Entity1
Entity1
Score
Explosion
Microsoft
Seatle
0.7
Explosion
Seatle
Microsoft
0.7
614
Validation
Module
606
616
An Explosion Occurred in
Microsoft Seattle

FIG. 6

EVENT DETECTION THROUGH TEXT ANALYSIS USING DYNAMIC SELF EVOLVING/LEARNING MODULE

CROSS-REFERENCE TO RELATED APPLICATIONS

This non-provisional patent application claims the benefit of U.S. Provisional Patent Application Ser. No. 61/910,818, entitled "Event Detection Through Text Analysis Using Dynamic Self Evolving/Learning Module," filed on Dec. 2, 2013, which is incorporated herein by reference in its entirety.

This application is related to U.S. patent application Ser. No. 14/558,300, entitled "Event Detection Through Text Analysis Using Trained Event Template Models," filed Dec. 2, 2014, now U.S. Pat. No. 9,177,254, which is hereby incorporated by reference in its entirety.

FIELD OF THE DISCLOSURE

The present disclosure relates in general to information data mining from media sources, and more specifically to a self-building event concept store for use in event detection, extraction and validation from different data sources.

BACKGROUND

The internet provides several sources of information which may be exploited. Internet news feeds and websites that allow users to interact with one another have exploded in popularity in the last few years. news feed channels such as CNN®, social networking websites sites such as Facebook® or LinkedIn®, and microblogging websites such as Twitter® enjoy widespread use. Millions of users post messages, images and videos on such websites on a daily, even hourly basis. Often, information gathered from these sources may refer to events taking place in real time. Such publicly accessible media may serve as a rich mine of information that may be used in different applications. For example, consider a scenario where a wide area emergency such as an earthquake or a flood has occurred and conventional emergency service lines are stressed beyond capacity; in this case users may turn to social media in order to request assistance. Another example of an event taking place in real time may be news feed reporting on civilians trapped under a building.

The high proliferation of information generated by media sources makes proper identification of events troublesome. New event types may continually emerge and may be hard to detected due to lack of information.

Thus, a need exists for a method of detecting and building new event models from one or more information sources.

SUMMARY

The system allows for the detection of events happening, and the proper association of those detected event to disambiguated entities using text analysis applied against different sources of information, which may be publishing data streams containing the information in a machine-readable digital format. Systems and methods described herein provide processes of learning different event types by extracting entities and topic vectors from a data source, such as a machine-readable word processing file, and comparing extracted entities and topic vectors against records of entities and topic vectors stored in a knowledgebase. The system may determine whether "new knowledge" has been identified in the extracted entities and topic vectors if the system determines that a particular combination of events, topics, and entities does not exist in the records within the knowledgebase; and so a new records for the new knowledge is generated. Embodiments may validate the new knowledge (combination of extracted entities, topics, and events) based on frequency of occurrence in a corpus.

In one embodiment, a computer-implemented method comprises identifying, by a computer, one or more features of a data stream associated with a data source, wherein at least one feature is an event candidate; automatically determining, by the computer, whether the one or more features identified in the data stream satisfy one or more event models in a categorization table, based upon the computer comparing the one or more features of the data stream against the one or more event models, wherein the event concept store comprises a non-transitory machine-readable memory storing the one or more event models; and responsive to the computer determining that the one or more features from the data stream fail to satisfy at least one event model in at least one categorization table stored in the event concept store: comparing, by the computer, the one or more features against one or more uncategorized event models in an uncategorized event table stored in the event concept store; and storing, by the computer, the one or more features as a new uncategorized event model in the uncategorized event table, in response to determining the one or more features fail to satisfy at least one uncategorized event model.

In another embodiment, a system comprising one or more nodes storing one or more event models, one or more event categorization tables, and an uncategorized event table, wherein each event model is associated with an event candidate and further comprises a threshold event score and a set of one or more features, wherein each event categorization table comprises one or more known event models, and wherein the uncategorized event table comprises a set of one or more features, a set of one or more entities, and a set of one or more topics, each associated with one or more uncategorized event models; and an event category validation processor configured to: receive a set of extracted features, a set of extracted entities, and a set of extracted topics; compare each of the sets with the one or more event categorization tables to determine whether the extracted features, entities, and topics, correspond to a known event model; and then compare each of the sets with the uncategorized event table to determine whether the extracted features, entities, and topics, correspond with an uncategorized event model.

Additional features and advantages of an embodiment will be set forth in the description which follows, and in part will be apparent from the description. The objectives and other advantages of the invention will be realized and attained by the structure particularly pointed out in the exemplary embodiments in the written description and claims hereof as well as the appended drawings.

It is to be understood that both the foregoing general description and the following detailed description are exemplary and explanatory and are intended to provide further explanation of the invention as claimed.

BRIEF DESCRIPTION OF THE DRAWINGS

The present disclosure can be better understood by referring to the following figures. The components in the figures are not necessarily to scale, emphasis instead being placed upon illustrating the principles of the disclosure. In the figures, reference numerals designate corresponding parts throughout the different views.

FIG. **1** is a high level functional view of an event extraction system, according to an embodiment.

FIG. **2** is a flow diagram illustrating a process by which events and entities from different sources are extracted, validated and stored, according to an embodiment.

FIG. **3** is component diagram for a dynamic event concept store, according to an embodiment.

FIG. **4** is workflow diagram illustrating the process of self learning of a dynamic event concept store, according to an embodiment.

FIG. **5** is an example embodiment of a detailed event extraction process using an event concept store, according to an embodiment.

FIG. **6** is an example embodiment of an event and entity extraction and validation using different data sources.

DEFINITIONS

As used here, the following terms may have the following definitions:

"Entity extraction" refers to information processing methods for extracting information such as names, places, and organizations.

"Corpus" refers to a collection of one or more documents.

"Features" is any information which is at least partially derived from a document.

"Event Concept Store" refers to a database of Event template models.

"Event" refers to one or more features characterized by at least its occurrence in time.

"Event Model" refers to a collection of data that may be used to identify a specific type of event.

"Module" refers to a computer or software components suitable for carrying out at least one or more tasks.

"Event Model Candidate" refers to the possible event model that may match a real event referenced in a data source.

DETAILED DESCRIPTION

The present disclosure is here described in detail with reference to embodiments illustrated in the drawings, which form a part here. Other embodiments may be used and/or other changes may be made without departing from the spirit or scope of the present disclosure. The illustrative embodiments described in the detailed description are not meant to be limiting of the subject matter presented here.

Reference will now be made to the exemplary embodiments illustrated in the drawings, and specific language will be used here to describe the same. It will nevertheless be understood that no limitation of the scope of the invention is thereby intended. Alterations and further modifications of the inventive features illustrated here, and additional applications of the principles of the inventions as illustrated here, which would occur to one skilled in the relevant art and having possession of this disclosure, are to be considered within the scope of the invention.

The present disclosure describes a system and method for detecting, extracting and validating events from a plurality of sources. Sources may include news sources, social media websites and/or any sources that may include data pertaining to events.

A system and method for detecting events based on input data from a plurality of sources such as, social media, news feeds and/or a corpus of documents is disclosed. The system may include a self learning event concept store that may store pre-determined event models and detect and build new event models based on input data from a plurality of sources. The system may receive input from a plurality of sources in the way of natural language unstructured text containing information about real time events. The system may use natural language processing techniques in order to separate individual entities and keywords and topic extraction techniques to identify topics. The process may then proceed with an entity disambiguation step and identify specific entities the source may be referring. The system may then identify independent events and associate them with the specific entities identified in the same data source. The process may then validate events based on overlapping and co-occurrence of events and entities from other data sources.

The system allows for the detection of events happening, and their proper association to disambiguated entities through text analysis of different sources.

Various embodiments of the systems and methods disclosed here collect data from different sources in order to identify independent events.

FIG. **1** shows components of a system **100** comprising external data sources **106**, **108** communicatively coupled over a network **104** to an event extraction system **102**. Event extraction system **102** may receive data from a plurality of data sources **106**, **108** through a network **104**. Non-limiting examples of data sources **106**, **108** may include social media **106**, subscription or news sources **108**, though other data sources **106**, **108** that store and/or publish information may be implemented such as, for example, a document corpus of historical events. Such data sources **106**, **108** may store and/or publish machine-readable data representing unstructured texts such as, for example, Tweets® (i.e., text strings), a news article, or a Facebook® status message.

A network **104** may be a connection between the different sources and event extraction system **102** through the Internet or an intranet. The network **104** may comprise any suitable collection of hardware and software components (e.g., network interface cards, routers, switches, firewalls, antennas, towers, hubs, trunks) capable of supporting networked communications between computing devices through any suitable protocol (e.g., TCP/IP, 3G, 4G, Bluetooth).

Event extraction system **102** may include a plurality of components (not illustrated in FIG. **1**) capturing and processing data received from a plurality of data sources **106**, **108**. Event extraction system **102** may comprise software with programmatic logic that may process inputs from the data sources **106**, **108**, and then identity and extract independent events and entities. Event extraction system **102** may be implemented in a single server computer or in a distributed architecture across a plurality of server computers.

Event extraction system **102** may store extracted events in event store **110**. Event store **110** may be a database implemented in known in the art database management systems (DBMS) such as, for example, MySQL®, PostgreSQL, SQLite, Microsoft SQL Server®, Microsoft Access®, Oracle®, SAP®, dBASE, FoxPro®, IBM DB2®, LibreOffice Base®, FileMaker Pro®, and/or any other type of database that may organize collections of data. Event store **110** may also be a No-SQL database such as, for example, MongoDB®, Couchbase®, H-Base®, Cassandra®, Accumulo®, and/or any other type of database that may organize collections of data.

Data sources **106**, **108** may be any form of computing service that stores, publishes, transmits, or otherwise makes available over a network **104** data representing information about events and entities. Data sources **106**, **108** may comprise one or more computing devices, servers, and other computing hardware capable of storing data, such as a database, and publishing data over a network **104**, such as a webserver. Non-limiting examples of data sources **106**, **108** may include social media networks **106**, online news sources **108**, blogs, educational portals (e.g., Blackboard®, online university libraries), online journals and magazines, among others. Social media **106** may be any computing service hosting on one or more servers information exchanges between users. Social media **106** users may publish webpages containing text, hyperlinks, and/or other forms of media that is then viewable by other users. New sources **108** may be any computing service hosting on one or more servers a web-based new outlet that publishes webpages containing text, hyperlinks, and/or other forms of media. Data sources **106**, **108** may publish data containing information that may be received and analyzed by an event extraction system **102** via webpages (e.g., HTML, PHP), RSS, e-mail, SMS, or other suitable protocol for publishing information across a computing network **104**.

FIG. **2** is a flow diagram of an event extraction method **200** according to an embodiment. Event extraction method **200** may begin when data is received from one or more data sources **202**. Data sources **202** may include social media computing services **202***a*, web-based news sources **202***b*, and/or any other data sources **202***c* that store and/or publish data containing information related to events.

In a first step **218**, after event extraction system receives data from one or more data sources **202**, event extraction system may perform event, topic and entity extraction, which may include the sub-steps **204** (pre-processing and data normalization), **206** (entity and topic extraction, and disambiguation), and **208** (event extraction).

In a first sub-step **204**, pre-processing and data normalization may be performed by a software module implemented on a computer as part of an event extraction system performing event, topic and entity extraction **218**. A module performing pre-processing and data normalization, first sub-step **204**, may contain programmatic logic, which may involve the use of natural language processing techniques (NLP) for identifying key features in data received from a data source **202**. Non-limiting examples of NLP techniques may include removing stop words, tokenization, stemming and part-of speech tagging among others know in the art.

In a next sub-step **206**, after a pre-processing and data normalization sub-step **204**, normalized pre-processed data may go through an entity/topic extraction and disambiguation, in which a software module of the event extraction system may identify and extract entities from the data and disambiguate independent entities from one another. Non-limiting examples of entities may include people, organizations, geographic locations, medical conditions, weapons, dates, time or any other entities. Entity and topic identification, extraction, and disambiguation of sub-step **206**, may be performed by one or more software module implemented in a computer as part of event extraction system.

In a simultaneous, subsequent, or previous sub-step **208**, an event extractor software module may identify possible event model candidates in the text received from the data source **202**. Different types of events may include an accident (e.g., car accident, a train accident, etc.), a natural disaster (e.g., an earthquake, a flood, a weather event, etc.), a man-made disaster (e.g., a bridge collapse, a discharge of a hazardous material, an explosion, etc.), a security event (e.g., a terrorist attack, an act of war, etc.), a major sporting event or concert, election day coordination, traffic incident, and/or any other event. Latent Dirichlet Allocation (LDA), or other methods of detecting and extracting events may be used to extract events. The event extractor module performing sub-step **208** may be executed in conjunction with an event concept store **210**. Event concept store **210** may be a database residing on any suitable computing device comprising non-transitory machine-readable storage media that stores event models. Event models may be compared against event model candidates identified in data. That is, in sub-step **208**, the event extractor module may identify types of features, which in this example are keywords, in the normalized pre-processed data received from the data source **202**, and compare the features against event models stored in the event concept store **210**. The event extractor module may then compute a likelihood score representing the likelihood a set of features (e.g., keywords) pertains to a certain event model, based on comparing the features against each of the event models stored in the event concept store **210**. In some implementations, a comparison between features of a event model candidate and a event model yielding a score between determined thresholds may indicate that the event model being compared is actually referenced in the data source.

In a next step **212**, after event, topic, and entity extraction of step **218**, the process may perform a spatial-temporal event grouping of extracted events and entities. That is, entities extracted from a data received from a data source **202***b* as a result of executing step **206** (entity extraction and disambiguation), and event model candidates identified in data step **202***b* during execution of step **208** (event extraction) may be associated together, as a spatial-temporal grouping, and then stored in non-transitory machine-readable storage memory. In cases having a plurality of data sources **202***a-c*, event model candidates identified in other data sources **202***a*, **202***c* and entities extracted from other data sources **202***a*, **202***c* may also be associated with one another, and then included to the spatial-temporal event grouping.

In a next step **214**, after generating spatial-temporal event groupings based on entities and event model candidates extracted from data sources **202**, software modules may perform event validation on the event model candidates in the spatial temporal event groupings. Event validation modules may compare spatial-temporal groupings (i.e., event model candidates and associated entities) extracted from different data sources **202***a-c* in order to determine whether a particular event model candidate extracted from a particular data source **202***b* resembles a real-time event being referenced in the different data sources **202***a*, **202***c*. Spatial-temporal groupings of different data sources **202***a*, **202***c* resembling a co-occurrence of event model candidates and entities of the particular data source **202***b* being validated may serve as validation that the event model candidate of the data source **202***b* resembles the event occurring in real-time.

Once validated in step **214**, the event model candidate and the associated entitles extracted from the data source **202***b* may be stored into a verified event store **216** database. For example, a server publishing text strings of a Twitter® feed may contain information describing a car accident in Washington D.C., while a news feed channel (e.g., text-based RSS) may contain text strings describing a car accident and high traffic jam in an area nearby the location referenced in the Twitter® feed. In this example of step **214**, an event validation software module may calculate a probability score that both text-based streams of data are describing the same real-world event. When the probability score reaches an established threshold, the event may be considered verified and thus stored into the verified event store **216**.

In some embodiments, a verified event store **216** may be used by different applications in order to query for different events depending on the purpose of the application. For example, an emergency service application may query for events related to vehicle accidents, fires and the like in order to provide first responders assistance. Another example may be a sports application which may query the database in order to determine the latest information in the NFL® Super Bowl®.

Event notification **220** may be used to push notifications or alerts to subscribers who wish to be notified immediately when events are verified. Once an event is verified, any subscribers who wish to receive notifications for that event type will be notified of the verified event.

FIG. **3** shows an internal view of a dynamic event concept store **310** of a system **300**, according to an exemplary embodiment.

A dynamic event concept store **310** may be a database that resides on any suitable computing device comprising non-transitory machine-readable storage media storing one or more event models. The event models stored in the event concept store **310** may be compared against event model candidates identified in data received from data sources. The event concept store **310** may store one or more event categorization table **302** components, uncategorized event table **304** components, and event category validation modules **306**. Event categorization tables **302**, uncategorized event tables **304** and event category validation modules **306** may be stored on a non-transitory machine-readable storage of a single computer. However, it should be appreciated that event categorization tables **302**, uncategorized event tables **304** and/or event category validation modules **306** may be distributed across multiple computers.

An event categorization table **302** may store records that contain previously identified event models, which the extraction module may retrieve to compare against text strings in data received from a data source, when extracting events from the data source.

An uncategorized event table **304** may store records containing keywords, entities, and/or topics that may be associated with a possible new unknown and/or unnamed event model and a probability score, which may serve as an indication of the likelihood that the keywords, entities, and/or topics represent a new event model.

An event category validation module **306** may be a software module executed by one or more suitable computing devices performing various tasks for validating event models. The event validation module **306** may receive a set of keywords, entities, and/or topics from a data source comprising data in the form of text strings. The event validation module **306** may then determine whether the keywords, entities, and/or topics in the set represent an existing event model or a possible previously unknown event model. Existing event models may be stored in records of an event categorization table **302**. Previously unknown event models may be stored in records of an uncategorized event table **304**.

FIG. **4** shows steps of a category validation process **400** executed by one or more computing devices of a system, according to an exemplary method embodiment.

Category validation process **400** may begin, in a first step **402**, when computers of the system receive data streams from one or more data sources and then extract one or more features (in this example the features are keywords) from the data streams.

In a next step **404**, a computer may compare keywords and/or other extracted features against event models stored in records of one or more event categorization tables, which may be stored in an event concept store. Based on the comparisons, the computer may automatically determine whether the keywords and features extracted from a data stream resemble existing event models stored in the event categorization tables.

In the event the computer determines that the keywords and/or other features extracted from the data of the data stream resembling, modeling, matching, or otherwise satisfying a known event model in an event categorization table, then the computer may execute a next step **406**. In the resulting step **406**, the computer may extract or otherwise identify which of the event models determined to resemble or model an event candidate extracted or identified in the data. That is, the extracted keywords and/or other features may resemble, model, or otherwise satisfy an event model associated with an event candidate. When the computer determines that the features satisfy the event model, then the computer extracts or otherwise identifies the event candidate from the data of the data stream. In some cases, the exemplary process **400** may come to an end, after the computer extracts or otherwise identifies the event candidate associated with the event model satisfied by the keywords and/or other features.

In the event the computer determines that the keywords and/or other features of the data do not resemble, model, match, or other satisfy any of the known event models stored in any of the event categorization tables, then the computer may perform an alternative optional step **408**. In next step **408**, the computer may compare the keywords and/or other features extracted or otherwise identified in the data against uncategorized event models stored in uncategorized event tables in the event concept store.

In the event the keywords and features do not resemble, model, match, or other satisfy an uncategorized event model stored in uncategorized event table, the computer may execute a optional step **410**. In the resulting step **410**, the keywords and features may be stored in a new record of an uncategorized event table of the event concept store. The new record of the keywords and features may represent a previously unknown or undiscovered event model, i.e., new knowledge, which may be compared against future keywords and/or features.

In the event the keywords and/or features resemble, model, match, or otherwise satisfy an uncategorized event model in the uncategorized event table, the computer may execute an alternative option step **412**. In the resulting step **412**, the probability score, or confidence score, associated with the uncategorized event model may be increased, thereby increasing the certainty that those particular keywords and features resemble an undiscovered event. That is, in some embodiments, the frequency at which a particular set of keywords and/or features may be used to validate a previously unknown or undiscovered event model, identified in one or more data streams. After the computer increases the confidence score of the uncategorized event model, the confidence score may be compared against a pre-determined threshold of the uncategorized event model. The pre-determined threshold of the uncategorized event model may be the minimum confidence score required to indicate that the set of keywords and features strongly resemble a real event type. Using the confidence score of the uncategorized event model, the computer may determine whether confidence score is higher than the pre-determined threshold.

In the event the computer determines the confidence score of the uncategorized event model is higher than or otherwise satisfies a threshold score for the event model, then in resulting step **414**, the computer may move the event model for the uncategorized event to an event categorization table. That is, the computer may remove a record of the event model from the uncategorized event table, and then store a record of the event model into an event categorization table. On the other hand, if the computer determines the confidence score is lower than or otherwise fails to satisfy the threshold score for the event model, then the process **400** may end.

FIG. **5** is an example embodiment of an event detection process **500**. An event extractor **506** may identify features, which in this example are keywords **502**, from a data input. In the illustrated example, the keywords "Bomb" and "Fire" are identified. The keywords may then be submitted for comparison against event models in the event concept store **510**. In this example, event concept store **510** may assign weights of 0.1 to "Bomb" and 0.3 to "Fire" for the event model of "Explosion". Event extractor **506** may then add up the weighted scores and determine if the resulting score exceeds a determined threshold. In this example a 0.4 score is generated for the probability of the event being an "Explosion"; however other methods of calculating weighted scores may be used and are included within the scope of this disclosure. Event extractor **506** may then transfer an event possibility of 0.4 of explosion to spatial-temporal event grouping **512**.

After pre-processing and normalization, entity extraction and disambiguation, and event extraction, each of the identified event model candidates and associated entities/topics from each of the different sources may be grouped together in a spatial-temporal event grouping **512**, which may be stored as a record of the spatial-temporal grouping **512**.

FIG. **6** is an example embodiment of an event grouping process **600**. The process may begin by taking an input from different data sources **602**. Each input from data sources **602** may go through an event, topic and entity extraction **618** process. Entities, topics and event model candidates **604** are extracted from the different data sources **602**. Entities, topics and event model candidates **604** from different data sources **602** may then be grouped together in spatial-temporal grouping **612** and an initial confidence score **606** may be assigned to each entity, topic and event model candidate **604** association.

Validation module **614** may compare the different records stored in the spatial-temporal grouping, and identify an overlap between entities and event model candidates **604** from each of the different data sources **602**. A score may be calculated using the initial confidence score **606** from the different entities and event model candidates **604** that overlap and/or repeat themselves in different data sources **602**. A score greater than a predetermined threshold may serve as an indication that the event model candidate **604** actually occurred. A verified event may then be stored in verified event store **616**. In the exemplary embodiment illustrated in FIG. **6** an overlap of entities "Microsoft" and "Seattle" are extracted along with the event model candidate "Explosion" from different sources this may serve as an indication that an explosion has occurred at Microsoft®, in Seattle.

In Example #**1** a tweet is extracted from Twitter® and ingested into the event extraction system **102**. The tweet contains the message "Bill Gates the chairman of Microsoft was Kidnapped in Syria". The process may go through pre-processing and data normalization **204** step where stop words are removed. The process may then continue and extract entities "Bill Gates", "chairman", "Microsoft", and "Syria," in entity/topic extraction and disambiguation **206** step and extract the event model "kidnapped" using event extraction method **200**. The entity extraction process may then identify Bill Gates as Chairman of Microsoft® and associate the entity with the event model for "kidnapped" in the spatial-temporal event grouping **212**.

Event validation **214** may then compare the "kidnapped" event model of Bill Gates to other events models from other sources also in spatial-temporal event grouping **212**. Event validation **214** may identify if other events models also refer to the "Kidnapping of the Chairman of Microsoft Bill Gates in Syria" and thus validate if the event is real. If the event is real it may be transferred to verified event store **216** where it may be used by other applications.

The foregoing method descriptions and the process flow diagrams are provided merely as illustrative examples and are not intended to require or imply that the steps of the various embodiments must be performed in the order presented. As will be appreciated by one of skill in the art the steps in the foregoing embodiments may be performed in any order. Words such as "then," "next," etc. are not intended to limit the order of the steps; these words are simply used to guide the reader through the description of the methods. Although process flow diagrams may describe the operations as a sequential process, many of the operations can be performed in parallel or concurrently. In addition, the order of the operations may be re-arranged. A process may correspond to a method, a function, a procedure, a subroutine, a subprogram, etc. When a process corresponds to a function, its termination may correspond to a return of the function to the calling function or the main function.

The various illustrative logical blocks, modules, circuits, and algorithm steps described in connection with the embodiments disclosed herein may be implemented as electronic hardware, computer software, or combinations of both. To clearly illustrate this interchangeability of hardware and software, various illustrative components, blocks, modules, circuits, and steps have been described above generally in terms of their functionality. Whether such functionality is implemented as hardware or software depends upon the particular application and design constraints imposed on the overall system. Skilled artisans may implement the described functionality in varying ways for each particular application, but such implementation decisions should not be interpreted as causing a departure from the scope of the present invention.

Embodiments implemented in computer software may be implemented in software, firmware, middleware, microcode, hardware description languages, or any combination thereof. A code segment or machine-executable instructions may represent a procedure, a function, a subprogram, a program, a routine, a subroutine, a module, a software package, a class, or any combination of instructions, data structures, or program statements. A code segment may be coupled to another code segment or a hardware circuit by passing and/or receiving information, data, arguments, parameters, or memory contents. Information, arguments, parameters, data, etc. may be passed, forwarded, or transmitted via any suitable means including memory sharing, message passing, token passing, network transmission, etc.

The actual software code or specialized control hardware used to implement these systems and methods is not limiting of the invention. Thus, the operation and behavior of the systems and methods were described without reference to the specific software code being understood that software and control hardware can be designed to implement the systems and methods based on the description herein.

When implemented in software, the functions may be stored as one or more instructions or code on a non-transitory computer-readable or processor-readable storage medium. The steps of a method or algorithm disclosed herein may be embodied in a processor-executable software module which may reside on a computer-readable or processor-readable storage medium. A non-transitory computer-readable or processor-readable media includes both computer storage media and tangible storage media that facilitate transfer of a computer program from one place to another. A non-transitory processor-readable storage media may be any available media that may be accessed by a computer. By way of example, and not limitation, such non-transitory processor-readable media may comprise RAM, ROM, EEPROM, CD-ROM or other optical disk storage, magnetic disk storage or other magnetic storage devices, or any other tangible storage medium that may be used to store desired program code in the form of instructions or data structures and that may be accessed by a computer or processor. Disk and disc, as used herein, include compact disc (CD), laser disc, optical disc, digital versatile disc (DVD), floppy disk, and blu-ray disc where disks usually reproduce data magnetically, while discs reproduce data optically with lasers. Combinations of the above should also be included within the scope of computer-readable media. Additionally, the operations of a method or algorithm may reside as one or any combination or set of codes and/or instructions on a non-transitory processor-readable medium and/or computer-readable medium, which may be incorporated into a computer program product.

The preceding description of the disclosed embodiments is provided to enable any person skilled in the art to make or use the present invention. Various modifications to these embodiments will be readily apparent to those skilled in the art, and the generic principles defined herein may be applied to other embodiments without departing from the spirit or scope of the invention. Thus, the present invention is not intended to be limited to the embodiments shown herein but is to be accorded the widest scope consistent with the following claims and the principles and novel features disclosed herein.

While various aspects and embodiments have been disclosed, other aspects and embodiments are contemplated. The various aspects and embodiments disclosed are for purposes of illustration and are not intended to be limiting, with the true scope and spirit being indicated by the following claims.

What is claimed is:

1. A computer-implemented method comprising:

identifying, by a computer, a plurality of features in a data stream associated with a data source;

assigning, by the computer, an initial confidence score to each respective feature of the plurality of features;

determining, by the computer, a candidate score of one or more features of the plurality of features using the initial confidence score of each respective feature in the one or more features, based upon a number of occurrences of each respective feature identified in the one or more features;

identifying, by the computer, an event candidate when the candidate score of the one or more features satisfies a predetermined threshold, wherein the event candidate is defined by the one or more features;

automatically determining, by the computer, whether the one or more features identified in the data stream as the event candidate satisfy one or more event models in a categorization table, based upon the computer comparing the one or more features of the data stream against the one or more event models, wherein an event concept store comprises a non-transitory machine-readable memory storing the one or more event models; and

responsive to the computer determining that the one or more features from the data stream fail to satisfy at least one event model in at least one categorization table stored in the event concept store:

comparing, by the computer, the one or more features against one or more uncategorized event models in an uncategorized event table stored in the event concept store wherein the uncategorized event table store records associated with new unknown event models;

storing, by the computer, the one or more features as a new uncategorized event model in the uncategorized event table, in response to determining the one or more features fail to satisfy at least one uncategorized event model;

generating, by the computer, an increased confidence score of an uncategorized event model of the one or more uncategorized event models in the uncategorized event table when the one or more features satisfy the uncategorized event model of the one or more uncategorized event models in the uncategorized event table;

calculating, by the computer, a probability score for the event candidate based on a likelihood that the one or more features represent a new event model;

comparing, by the computer, the increased confidence score of the event candidate and the probability score of the event candidate with a pre-determined threshold score of the uncategorized event model of the one or more uncategorized event models in the uncategorized event table; and

storing, by the computer, the uncategorized event model in the categorization table when the increased confidence score and the probability score is higher than or matches the pre-determined threshold score.

2. The method according to claim 1, further comprising receiving, by the computer, one or more data streams from one or more data sources.

3. The method according to claim 1, wherein determining whether the one or more features identified in the data stream satisfy at least one of the one or more event models further comprises:

automatically comparing, by the computer, the one or more features against the one or more event models of one or more categorization tables stored in the event concept store.

4. The method according to claim 3, further comprising:

automatically identifying, by the computer, a subset of one or more features from the one or more features, according to an event model of the one or more event models; and

determining, by the computer, a score for the subset of the one or more features, based on a weight assigned to each respective feature in the subset according to the event model.

5. The method according to claim 4, wherein each respective feature of the subset of the one or more features satisfies a threshold value of the event model.

6. The method according to claim 1, further comprising:
determining, by the computer, whether the one or more features identified in the data stream satisfy an event model in the categorization table; and
automatically identifying, by the computer, in one or more categorization tables an event model associated with the event candidate, in response to determining that the one or more features satisfy the event model of the one or more event categorization tables.

7. An event extraction system comprising:
an event concept store that comprises a non-transitory machine-readable memory storing one or more event models, one or more event categorization tables, and an uncategorized event table,
wherein each event model of the one or more event models is associated with an event candidate and further comprises a threshold event score and a set of one or more features,
wherein each event categorization table comprises one or more known event models, and
wherein the at least one uncategorized event table comprises a set of one or more features, a set of one or more entities, and a set of one or more topics, each associated with one or more uncategorized event models; and
an event category validation processor communicatively coupled to a network and executes an event extractor module configured to:
receive a set of extracted features, a set of extracted entities, and a set of extracted topics from a normalized pre-processed data stream associated with a data source, wherein at least one feature of the set of extracted features, the set of extracted entities, and the set of extracted topics is an event candidate;
assign an initial confidence score to the set of extracted features, the set of extracted entities, and the set of extracted topics;
calculate a score using the initial confidence score of the set of extracted features, the set of extracted entities, and the set of extracted topics that repeat themselves or overlap in different data sources;
determine that an event candidate occurred when the calculated score is greater than a predetermined threshold;
compare each of the sets in which the at least one feature is the event candidate with the one or more event categorization tables to determine whether the extracted features, entities, and topics, correspond to a known event model; and
compare each of the sets with the uncategorized event table to determine whether the extracted features, entities, and topics, correspond with at least one uncategorized event model, wherein the event extractor module is further configured to increase a confidence score corresponding to the at least one uncategorized event model when the set of extracted features are similar to the at least one uncategorized event model in the uncategorized event table, wherein the uncategorized event table store records associated with new unknown event models and a probability score indicating features representing new event models, and wherein the event extractor module is further configured to calculate a probability score indicating features, wherein the probability score is determined based on a likelihood that the features represents new event models; and store the at least one uncategorized event model as a new event model in the one or more event categorization tables responsive to determining the confidence score and the probability score corresponding to the at least one uncategorized event model satisfies a threshold score.

8. The system according to claim 7, wherein the event extractor module is further configured to:
automatically identify a subset of one or more features from the set of extracted features, according to an event model of the one or more event models; and
determine a score for the subset of the one or more features, based on a weight assigned to each respective feature in the subset of one or more features according to the event model of the one or more event models.

9. The system according to claim 8, wherein each respective feature of the subset of one or more features of the set of extracted features satisfies a threshold value of the event model of the one or more event models.

10. The system according to claim 7, wherein the set of extracted features are identified in a data stream associated with a data source.

11. The system, according to claim 10, wherein the event extractor module is further configured to determine whether the set of extracted features identified in the data stream satisfy an event model of the one or more event models in an event categorization table of the one or more event categorization tables; and
automatically identify in the one or more event categorization tables the event model associated with the event candidate, in response to determining that the set of extracted features satisfy the event model of the one or more event categorization tables.

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